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HUMAN INTELLIGENCE BASED DEEP LEARNING TECHNIQUE FOR IMAGE SEGMENATION OF BRAIN MRI

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ABSTRACT
In this work, a fully automated system for brain region segmentation by using Human intelligence based deep learning technique is proposed. Deep learning technique is most popular state of the art method in recent applications. There are two stages involved the pre-processing and segmentation via Convolutional Neural Network (CNN).The MRI image with noise is used as an input image. MRI images are collected from publicly available database Open Access Series of Image Studies (OASIS). Three layers are used in this network, which is used to segment the brain region. The MR images are first given to pre-processing step to enhance the quality of image for segmentation. In this work, Non Local Mean Filter is used for image denoising which calculates weighted average of pixels and finding similarity with the target pixel. The denoised image is given as an input of CNN. Brain region segmentation by deep learning involves feature extraction. CNN learns features directly from an image and no handcrafted features are needed. The method consists of three steps such as input data generation, construction of model and learning the parameter. So, a compact representation from the image as image patches are given as input data to the multilayer convolutional neural network. The supervised deep network consists of three layers. Input image is given to the input layer, it predict the label from input layer. In every hidden layer one convolutional layer and one pooling layer is Present. Convolutional layer compute a dot product of the weights, input, and add a bias term. In this work 4 training images and 1 testing images in ages from the database are used. CNN is trained iteratively with representative input patterns along with target label. The execution of the CNN gives high exactness in the scope of 94% to 96%.
Key Words - Deep Learning, CNN, Image Segmentation, Brain MRI, accuracy.

1. Introduction
Cancer can be defined as the uncontrolled, unnatural growth and division of the cells in the body. Occurrence, as a mass, of these unnatural cell growth and division in the brain tissue is called a brain tumor. While brain tumors are not very common, they are one of the most lethal cancers. Depending on their initial origin, brain tumors can be considered as either primary brain tumors or metastatic brain tumors. In primary ones, the origin of the cells are brain tissue cells, where in metastatic ones cells become cancerous at any other part of the body and spread into the brain. Gliomas are type of brain tumors

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that originate from glial cells. They are the main type of brain tumors that current brain tumor segmentation research focuses on. The term glioma is a general term that is used to describe different types of glioma ranging from low-grade Gliomas like astrocytomas and oligodendrogliomas. To the high grade (grade IV) glioblastoma multiform (GBM), which is the most aggressive and the most common primary malignant brain tumor2. Surgery, chemotherapy and radiotherapy are the techniques used, usually in combination, to treat gliomas3. Early diagnosis of glioma plays an important role in improving treatment possibilities. Medical Imaging techniques such as Computed Tomography (CT), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS) and Magnetic Resonance Imaging (MRI) are all used to provide valuable information about shape, size, location and metabolism of brain tumors assisting in diagnosis. While these modalities are used in combination to provide the highest detailed information about the brain tumors, due to its good soft tissue contrast and widely availability MRI is considered as the standard technique. MRI is a non-invasive in vivo imaging technique that uses radio frequency signals to excite target tissues to produce their internal images under the influence of a very powerful magnetic field. Images of different MRI sequences are generated by altering excitation and repetition times during image acquisition. These different MRI modalities produce different types of tissue contrast images, thus providing valuable structural information and enabling diagnosis and segmentation of tumors along with their subregions4. Four standard MRI modalities used for glioma diagnosis include T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted MRI with gadolinium contrast enhancement (T1-Gd) and Fluid Attenuated Inversion Recovery (FLAIR). During MRI acquisition, although can vary from device to device, around one hundred and fifty slices of 2D images are produced to represent the 3D brain volume. Furthermore, when the slices from the required standard modalities are combined for diagnosis the data becomes very populated and complicated.
Accurate diagnosis in medical procedure has attained using different imaging modalities such as Magnetic Resonance (MR) imaging, Computed Tomography (CT), digital mammography etc. These can provide very detailed and informative anatomy of a subject. According to these developments, diagnosis imaging became an important tool in diagnosis and planning treatment. Brain region segmentation is important first step in every neuroimaging applications such as tissues segmentation and volume calculation. Automatic skull removal is extremely difficult time consuming process because of complex boundaries and low contrast. Research community develops many methods.
Deep learning, otherwise called as deep structured learning is one of the machine learning algorithms. It learns data from the input image using either supervised or unsupervised. In this paper, supervised learning approach using Convolutional Neural Network is used for accurate brain region segmentation.

2. Literature Survey

In accordance to our survey the paper named “MRI Brain Image Segmentation and Detection Using KNN Classification”, scholar tried to only use the the k-Nearest Neighbour (k-NN) algorithm for the accuracy of the algorithm as

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85%. In one of survey the paper named “A new similarity measure for non-local means filtering of MRI Images”, scholar tried to only denoise the MR Images. And project’s named Deep MRI brain extraction: A 3D CNN for skull stripping, Fully CNN for semantic segmentation, Brain tumor segmentation with deep neural network, Scholars have been trying to only segment the brain region to find the presence of cancer tumors and in turn to operate them. But because of noise present in the scanned MR Images, the segmentation done was not up to the mark and hence the surgeries too.

So to enhance the surgical results, before segmentation we are going to denoise the MR Images and then the segmentation follows. Because of denoising and then segmentation the results would be definitely better. In our work we are also trying to reduce or correct the intensity inhomogeneity present in MR Images. A paper named “A review of methods for correction of intensity inhomogeneity in MRI” the scholar tried to correct the intensity inhomogeneity in MR Images but, because of using gray images the correction was not achieved to the greater extent. If inhomogeneity is not corrected it will be simply transferred from one tissue to other and this can be obstacles during surgeries. In our work we are using gray images as well as colored images of the same taken gray images, so that the intensity inhomogeneity can be corrected to a great extent. As we are using colored images we could be able to definitely differentiate the intensity inhomogeneity and can get clear results, which can in turn helpful to the patients to attain best results in their surgery. Moreover our work is a combined work of all the above mentioned papers, where we are denoising the images first and then segmentation of brain region using the denoised images. Finally the segmented MR Images are going to convert from gray scale to colored scale so that the intensity inhomogeneity can be completely avoided. Hence by denoising, segmenting and correcting the intensity inhomogeneity, doctors would be able to get the best MRI scan images. If we have this kind of MRI, then definitely we can achieve the best and expected surgical results.

Implementation

Figure 1 shows proposed implementation

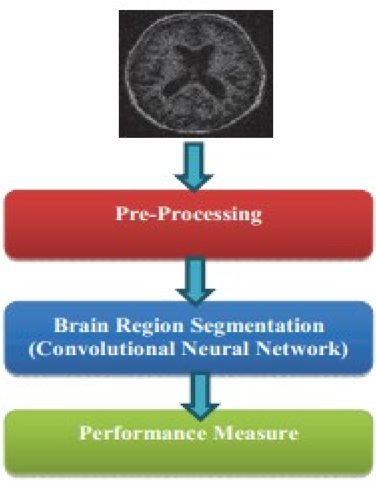

Figure 1: Flow Diagram of Proposed Methodology

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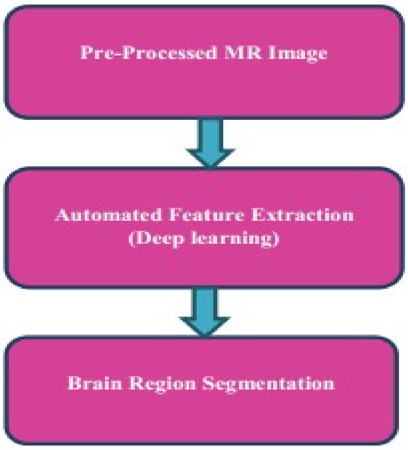

Figure 2:Brain Region Segmentation Steps

Figure 2 shows segmentations steps.

The architecture of "human –brain-inspired" deep nonlinear models compose complex features in the deeper layer of the network by analyzing the simple features learned in the previous layer. These features prove to be very effective descriptors in object recognition problems. During the training phase of these models, the features are encoded iteratively and then the learned weights are updated for improved optimization of the network. The features can be learned using CNN in supervised manner. The features learned in a layer wise method are fed into a trained classifier, which predicts the labels. The classifier being a supervised layer has been trained using a set of images along with the associated label. The trained network should be able to accurately predict the label for unseen images. The feature extraction using deep learning includes the following implementation steps: input generation, construction of the deep network, training the network and extracting the learned feature. The steps in feature extraction using CNN are shown in Fig. 3.

CNN learns features directly from an image and no handcrafted features are needed. The method consists of three steps such as input data generation, construction of model and learning the parameter. So, a compact representation from the image as image patches are given as input data to the multilayer convolutional neural network. The supervised deep network consists of three layers. Input image is given to the input layer, it predict the label from input layer. In every hidden layer one convolutional layer and one pooling layer is Present. Convolutional layer compute a dot product of the weights, input, and add a bias term. In gray image, the bias term is always one. Pooling layer perform down sampling operation, it reduces the number of connections to the following layer.

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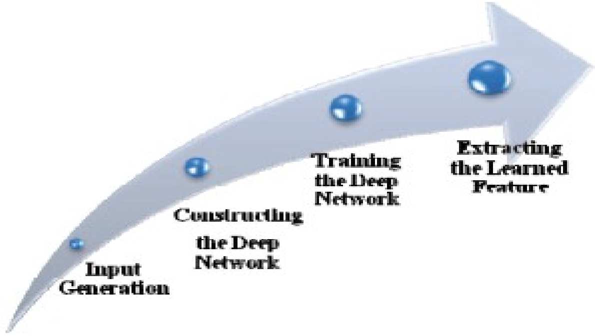

Figure 3: Steps in Feature Extraction using CNN

A CNN is different from the ordinary back propagation neural network (BPN) because a BPN works on extracted handcrafted image features whereas, a CNN works directly an image to extract useful, and necessary features for segmentation. A CNN consists of a number of convolutional layers, pooling layers and fully connected layers followed by one classification layer. When the size of the image is given as input to the CNN feature maps are produced by convolving the image with the filters. Each map is sub-sampled typically with mean or max pooling layers. Sub sampling rate usually varies from two to five. After the convolutional layers, there may be any number of fully connected layers. The implementation steps are input generation, constructing the deep network, training the deep network and extracting the learned features. CNN can be done in three ways. The first method is to build and train the CNN to obtain feature. The second method is to use “off-the-shelf CNN features” without retraining the CNN. The third method is to use CNN in fine-tuning the results obtained using deep learning model. The first technique is used in building the CNN in this work. The CNN is constructed with 3 layers as shown in Fig. 4. In each hidden layer one convolutional layer and one pooling layers are present followed by one fully connected layer. It combines all the features learned by the previous layer across the image to identify the larger pattern.

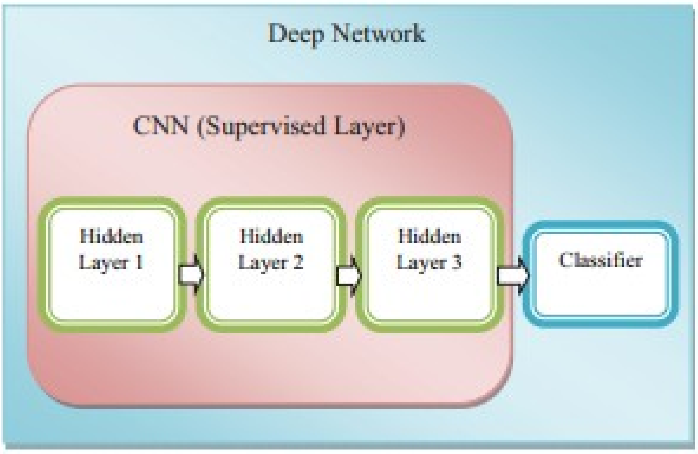

Figure 4: Construction of Convolutional Neural Network

RESULTS

The MRI images from publicly available OASIS Database were used in the

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supervised deep learning brain region segmentation. The OASIS is an organization of Washington research groups interested in the understanding of MRI and it has generated a database of digital MRI images. In this work 4 training images and 1 testing images in ages from the database are used.

CNN is trained iteratively with representative input patterns along with target label. Trained CNN is tested with unseen images. Fig. 5.1 to 5.4 shows the qualitative result of denoised and brain region segmentation images.

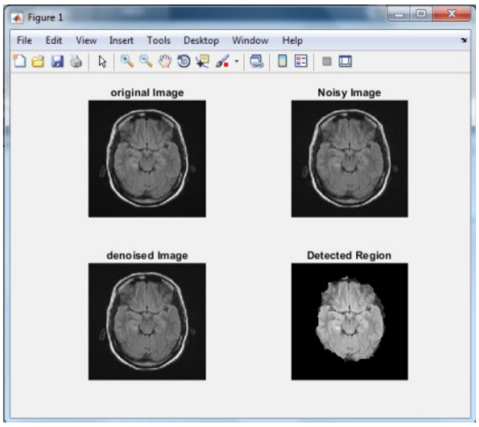

Figure 5.1(a):Brain Region Segmented Output Image

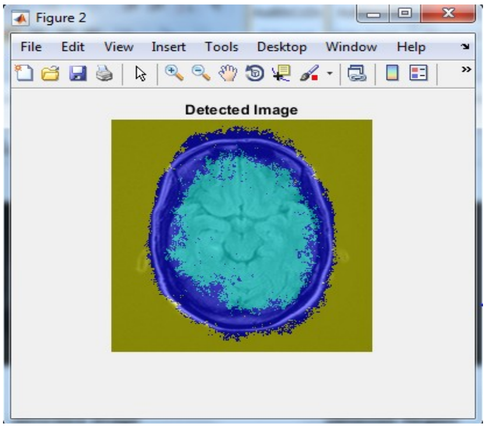

Figure 5.1(b): Detected image with transparency

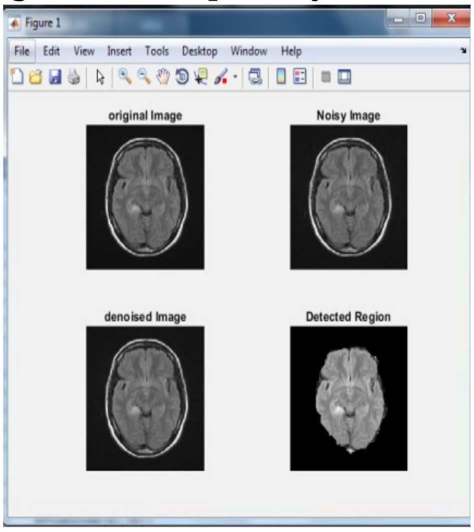

Figure 5.2(a):Brain Region Segmented Output Image

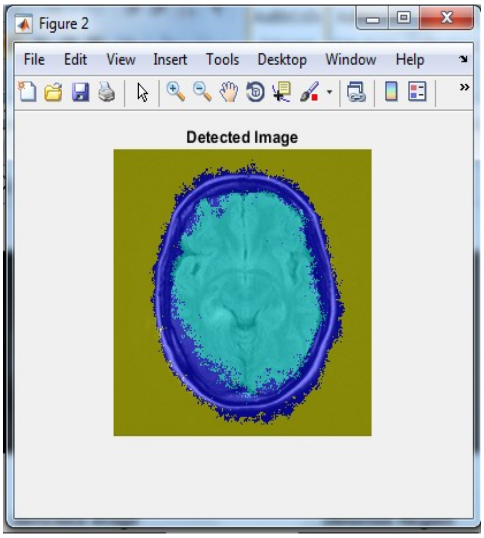

Figure 5.2(b): Detected image with transparency

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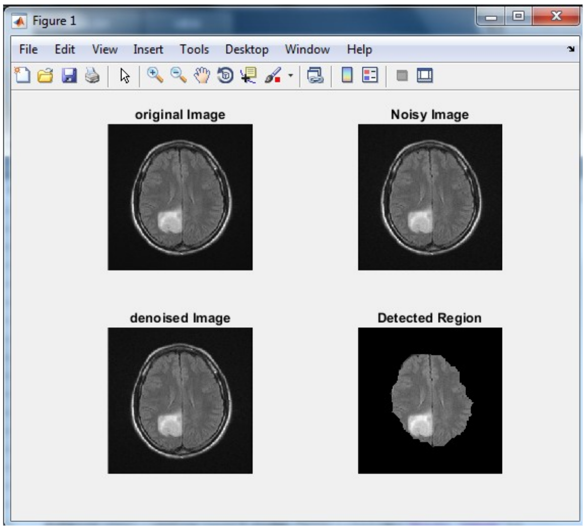


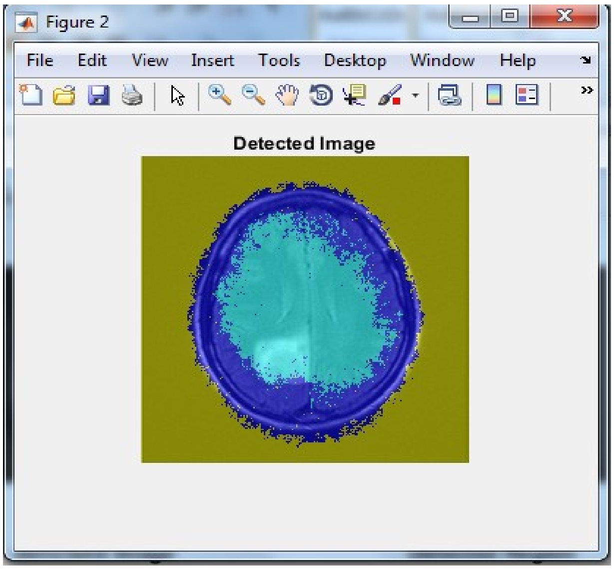
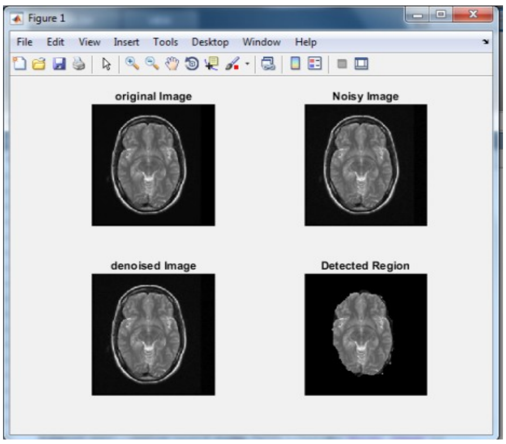


Figure 5.3(a):Brain Region Segmented Output Image **Figure 5.3(b): Detected image with transparency**



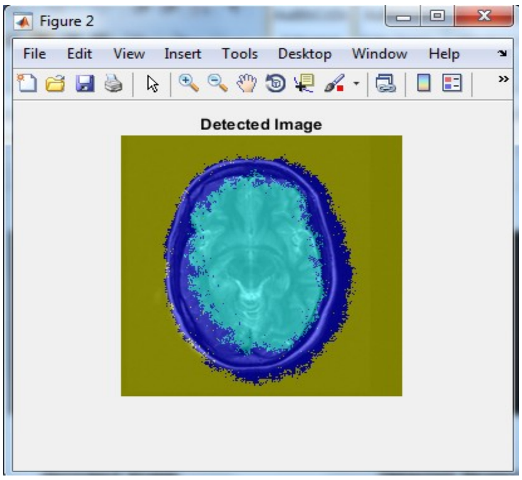


Figure 5.4(a):Brain Region Segmented Output Image **Figure 5.4(b):Detected image with transparency**

Table 1. QUANTITATIVE RESULTS FOR DENOISED IMAGE AND BRAIN REGION SEGMENTATION IMAGES

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INPUT IMAGES	DENOISED IMAGE PSNR (DB)	MSE	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
IMAGE 1	43.39	1.3610	0.9635	0.9545	0.9677
IMAGE 2	43.42	1.3443	0.9678	09586	0.9723
IMAGE 3	43.50	1.2922	0.9468	0.8348	0.9968
IMAGE 4	43.49	1.3004	0.9436	0.8473	0.9884

TABLE 2 QUANTITATIVE RESULTS FOR DENOISED IMAGE AND BRAIN REGION SEGMENTATION IMAGES

INPUT IMAGES	DENOISED IMAGE PSNR (DB)	MSE	ACC (%)	SE (%)	SPE (%)	SI	CDR	USE	OSE	TSE
Image1	43.39	1.361	0.9635	0.9545	0.9677	0.9433	0.9545	0.0693	0.0455	0.1148
Image2	43.42	1.344	0.9678	0.9586	0.9723	0.9513	0.9586	0.0569	0.0414	0.0982
Image3	43.50	1.292	0.9468	0.8348	0.9968	0.9064	0.8348	0.0072	0.1652	0.1724
Image4	43.49	1.300	0.9468	0.8473	0.9884	0.9051	0.8473	0.0248	0.1527	0.1776

Conclusion

In the proposed work, Convolutional Neural Network (CNN) is utilized for mind district division. The freely accessible MRI database called OASIS are utilized in this work The MRI pictures are first pre-prepared to expel Rician clamor by utilizing Non Local Mean (NLM) channel and non-mind tissues (skull partition) are evacuated by utilizing CNN. One of the benefit of CNN is no high quality highlights are required; it gains includes legitimately from the pictures. The execution of the CNN gives high exactness in the scope of 94% to 96%. In future work, the typical tissues, for example, white issue, dark issue, and cerebrospinal liquid can be fragmented by utilizing computational insight procedures. In view of the volume changes from these tissues, the scatters in cerebrum can be distinguished.

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